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Assessment of climate change impact on yield of major crops in the Banas River Basin, India

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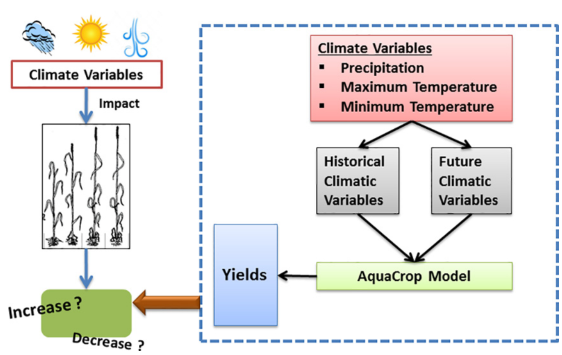
HIGHLIGHTS

- Three crops are used for future yield prediction in the basin.
- Variation in temperature and precipitation pattern will affect the crop yields.
- AquaCrop predicted crop yields in Banas Basin of future period 2021–2050.
- With the increase of CO_2 and temperature the crop yields show an increasing trend.

GRAPHICAL ABSTRACT



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ABSTRACT

Crop growth models like AquaCrop are useful in understanding the impact of climate change on crop production considering the various projections from global circulation models and regional climate models. The present study aims to assess the climate change impact on yield of major crops in the Banas River Basin i.e., wheat, barley and maize. Banas basin is part of the semi-arid region of Rajasthan state in India. AquaCrop model is used to calculate the yield of all the three crops for a historical period of 30 years (1981–2010) and then compared with observed yield data. Root Mean Square Error (RMSE) values are calculated to assess the model accuracy in prediction of yield. Further, the calibrated model is used to predict the possible impacts of climate change and CO_2 concentration on crop yield using CORDEX-SA climate projections of three driving climate models (CNRM-CM5, CCSM4 and MPI-ESM-LR) for two different scenarios (RCP4.5 and RCP8.5) for the future period 2021–2050. RMSE values of simulated yield with respect to observed yield of wheat, barley and maize are 11.99, 16.15 and 19.13, respectively. It is predicted that crop yield of all three crops will increase under the climate change conditions for future period (2021–2050).

1. Introduction

In the world, 80% of the agricultural area is covered by rain-fed agriculture and generates about 60% of the world food (FAO, 2008). Agricultural production is greatly affected by climatic factors like changes in greenhouse gas concentrations, radiation, water scarcity, precipitation and temperature. According to the Food and Agriculture Organization (FAO), world agricultural production growth is expected to decrease with annual rate of 1.5% by the year 2030 and then a further reduction by 0.9% till 2050, compared with 2.3% growth per year since 1961 (FAO, 2003). Climate change is posing significant change in water supply and further threats to food productivity in various parts of the world (Smith, 2013; Hanjra and Qureshi, 2010; Knox et al., 2012;

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Kummu et al., 2012). Climate change may affect the agriculture production and food security due to variation in the spatial and temporal distribution of rainfall and the availability of resources like water, land, capital, biodiversity, and terrestrial resources (Lin, 2011). In India, the total food production has increased at a much faster pace than the population in last few decades. Due to this, there is a huge stress on groundwater resources and degradation of land quality. Largely, the Indian agriculture and food production is highly vulnerable to climate change due to the high sensitive to monsoon variability. Lobell et al. (2012) found that the wheat growth in northern India is highly sensitive to temperature > 34 °C. The Intergovernmental Panel on Climate Change (IPCC, 2007) reported that 0.5 °C rise in winter temperature is likely to reduce wheat yield by 0.45 tons/ha in India (Easterling et al., 2007).

Crop simulation models have been widely used to simulate biomass and yield of different crops (Challinor et al., 2010; Rotter et al., 2011; Bird et al., 2016). AquaCrop is a crop water productivity simulation model developed by the Food and Agriculture Organization (FAO) of the United Nations (FAO, 2009; Hsiao et al., 2009; Steduto et al., 2009). Farahani et al. (2009) used the AquaCrop model for understanding the behavior of crop under full (100%) and deficit (40, 60, and 80% of full) irrigation regimes in the summer season of the Mediterranean environment of northern Syria. Abedinpour et al. (2012) simulated the AquaCrop model for kharif Maize crop in a semi-arid environment of India using two years (2009 and 2010) experimental data for model calibration and validation. The model predicted that the water productivity range from 2.35% to 27.5% for different irrigation and nitrogen levels. Mkhabela and Bullock (2012) calibrated and validated the AquaCrop model for wheat yield and total soil water content on the Canadian Prairies and observed that the simulation of wheat grain yield and soil water content are within acceptable range. Simba et al. (2013) used AquaCrop model for investigating climatic characteristics responsible for yield in the maize, sorghum and millet crop varieties and calibrated the model by using the parameter water balance, biomass production and yield. Saad et al. (2014) calibrated the AquaCrop model in Egypt to assess crop water productivity of maize crop under non saline and saline soil conditions. Singh et al. (2013) used the AquaCrop model to estimate the 10 varieties of wheat yield production under the full irrigation schedule during 2008–2009 and 2009–2010 at the farm of Uttar Banga Krishi Viswavidyalaya Dakshin Dinajpur District. Kumar et al. (2014) simulate the four wheat varieties grain yield and water productivity under the different salinity modules in the Water Technology Centre (WTC), Indian Agricultural Research Institute (IARI), New Delhi and found that the AquaCrop model gives the good prediction of yield as compared to the water productivity and biomass in the wheat grain. Pawar et al. (2017) used the calibrated AquaCrop model to evaluate the different irrigation schedules under mulch and non-mulch condition for cabbage plant and observed the 80% of the harvesting index of cabbage plant. Rajasthan receives about 80% of its total annual precipitation through monsoonal precipitation. The state is facing the challenge of limited water resources availability which is directly linked to the agriculture production and food security issues. The Banas River Basin is a seasonal river and covers almost half of the state area. Considering the location of the study area in the semi-arid climatic condition, it is highly vulnerable to climatic conditions, water availability, and agricultural productivity. This study is an attempt to understand the linkage between climate change, water and agriculture production. The present study aims to assess the climate change impacts on wheat, barley and maize crops in the basin, under past and future scenarios of Coordinated Regional Climate Downscaling Experiment–South Asia (CORDEX-SA), by coupling crop models with ensemble climate models scenarios. The main objective of the study is to predict the effect of climate change scenarios on the different crops using an ensemble mean of three climate models. Section 2 introduces the study area, whereas the materials and methods are presented in Section 3. Section 4 presents the results of climate change impacts on crop yield, followed by a discussion and conclusions in Section 5.

2. Study area description

The Banas River Basin is located in east-central Rajasthan, between latitudes 24°15′ and 27°20′ N and longitudes 73°25′ and 77°00′ E as shown in Fig. 1. The elevation of the study area lies between 176 m and 1305 m. It originates in the Khamnor hills of the Aravali range and flows along its entire length through Rajasthan (Department of Water Resources). It is bounded by the Luni Basin in the west, the Shekhawati, Banganga and Gambhir Basins in the north, the Chambal Basin in the east, and the Mahi and Sabarmati Basins in the south. Basin is covering an area of about 45,833 km^2 with a total length of about 512 km (Department of Water Resources). The Banas River covered the 13 districts namely, Sawai Madhopur, Jaipur, Ajmer, Tonk, Rajsamand, Banswara, Chittaurgarh, Udaipur, Bhilwara, Dausa, Nagaur, Sikar and Bundi.

In the Rajasthan state, there are three types of cereal grown, i.e. primary, secondary and principal. The average yield of principal cereals of Rajasthan is higher as compared to the primary and secondary cereals. The maize, wheat and barley come under the principal cereals, and cultured under the irrigation and confined to the limited area, but the secondary cereals are mostly grown under rain-fed conditions (Sen and Abraham, 1966). Fig. 2 shows the trends in crop yield of the maize, barley and wheat crops of the historical period (1981–2010) and it is observed that all the crops are showing an increasing pattern. In this study, only climate data are used as variable without changing the other parameters like seed variety, sowing date, soil characteristics, management practices, and irrigation practices.

According to the Agricultural Department of Rajasthan, the state has been divided into 10 agro-climatic zones. These zones have been classified on the basis of precipitation, temperature, topography, cropping pattern, soil characteristics and irrigation patterns. But the Banas Basin covers five agro-climatic zones that are shown in Table 1.

3. Materials and methods

In this study, secondary datasets are collected from the agricultural department and the Indian Meteorological Department (IMD). Data required for AquaCrop (crop development, irrigation schedule soil profile and ground water level) are collected from the agriculture department. Meteorological data includes daily maximum and minimum temperature, precipitation from the period 1981 to 2010. The evapotranspiration (ET_0) values are calculated by the ET_0 calculator and further used as an input in the crop model. Detailed flowchart and methodology framework is shown in Fig. 3. Future climate data is retrieved from the Coordinated Regional Climate Downscaling Experiment–South Asia (CORDEX-SA) and bias-correction are performed for the scenarios RCP4.5 and RCP8.5. The AquaCrop model is calibrated and validated for three different crops (wheat, maize and barley) for the period 2006 to 2010. Crop yield of three crops are predicted using bias-corrected climatic scenarios for future period 2021-2050.

3.1. Crop information

Maize crop is C4 plant and most important cereals for both human and animal consumption. The production of maize is about 594 million tons from about 139 million ha (FAOSTAT, 2000). In the present and future range of atmospheric CO_2 concentrations vary from 300 to 1000 μmol/mol (Goudriaan and Unsworth, 1990). According to the Cure (1985) and Cure and Acock (1986), the stomatal conductance and transpiration of the maize crop may decrease to 40% and 28% at high atmospheric CO_2 and light conditions. The maize crop is grown when the mean daily temperatures is above 15 °C. According to the FAO, the mean daily temperatures of the growing period is >20 °C and the maturation period of the early and medium grain varieties take 80–110 days and 110–140 days, respectively. When the mean daily temperature is below 20 °C, the maturation period extends up to 10–20 days.

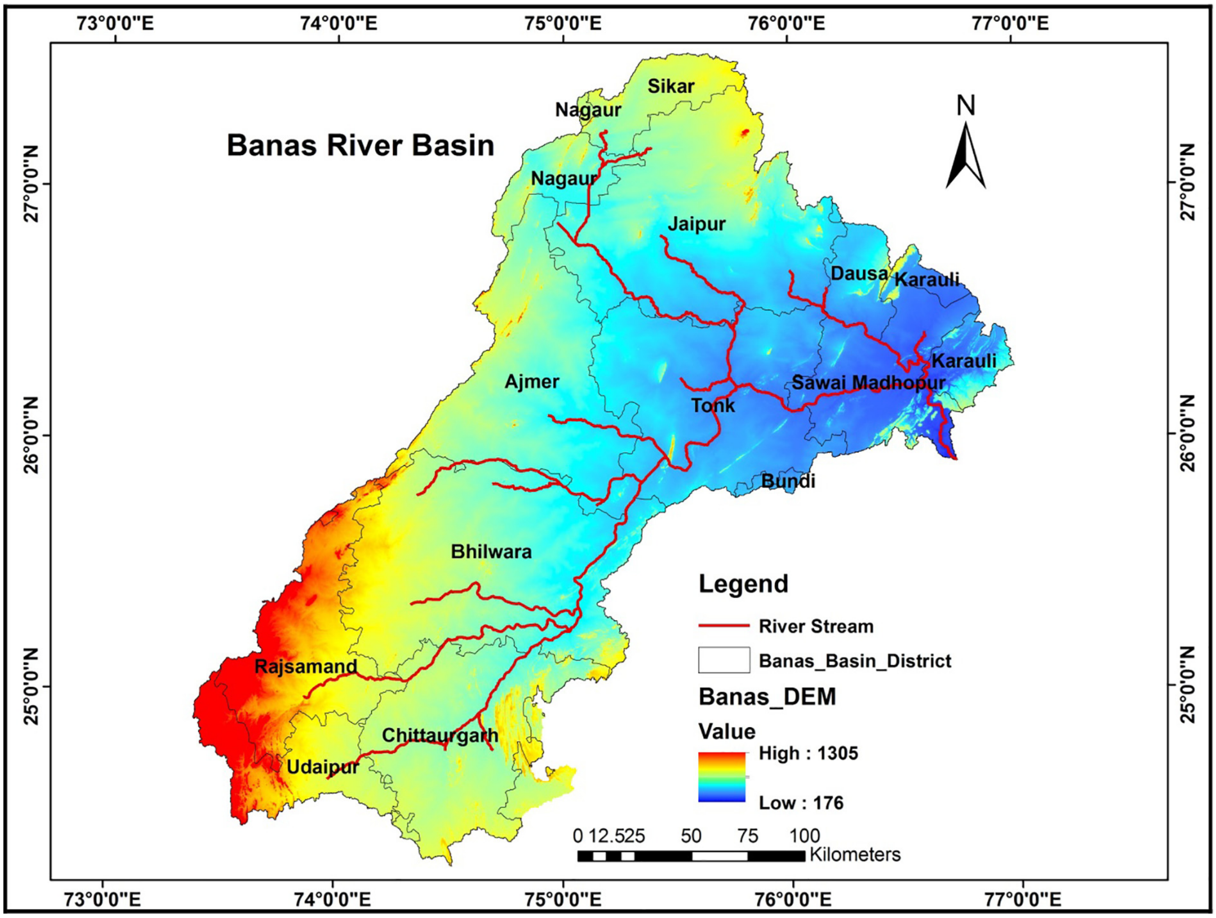

Fig. 1. Study area map of Banas River Basin, Rajasthan.

The wheat crop is grown in the spring and winter season. The crop length of spring wheat and winter wheat varies from 100 to 130 days and 180 to 250 days, respectively (Food and Agriculture Organization, United States). Wheat and barley are C3 plant and increase in atmospheric CO_2 affect the growth of the plants. Barley is cultivated as a rabi crop in the study area with the sowing in November–December and harvesting in March–May. Barley crop is mainly used in livestock feed, human food and barley malt for producing beer and alcohol. Table 2 presents the crop characteristics and developmental stage of the C3 and C4 plants.

3.2. Soil information

According to the Food and Agriculture Organization (FAO), the texture of soil varies from sandy loam, loam, clay loam, silt loam, and clay. Loamy soil covers >60% of the basin area. The major soils (common

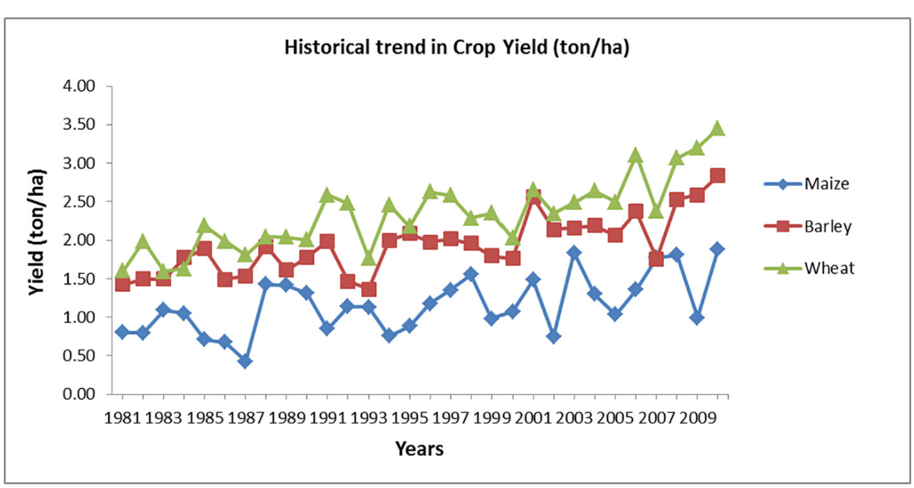

Fig. 2. Historical trends of the maize, barley and wheat crops of the periods 1981–2010.

Table 1
Details of five agro-climatic zones covered by the Banas River Basin.
Source: Agriculture Department of Rajasthan.

Zone	Area	Total area (million ha)	District covered	Major crops		Soils information
				Kharif	Rabi	
IIIA	Semi arid eastern plains	2.96	Jaipur, Ajmer, Dausa, Tonk	Pearl millet, cluster bean, sorghum	Wheat, mustard, gram	Sierozens, eastern part alluvial, west north west lithosols, foot hills, brown soils
IIIB	Flood prone eastern plain	2.77	Alwar, Dholpur, Bharatpur, Karoli, S. Madhopur	Pearl millet, cluster bean, groundnut	Wheat, barley, mustard, gram	Alluvial prone to water logging, nature of recently alluvial calcareous has been observed
IVA	Sub-humid southern plains	3.36	Bhilwara, Sirohi, Udaipur, Chittorgarh	Maize, pulses, sorghum	Wheat, gram	Soil are lithosols at foot hills & alluvials in plains
IVB	Humid southern plains	1.72	Dungarpur, Udaipur, Banswara, Chittorgarh	Maize, paddy sorghum black gram	Wheat, gram	Predominantly reddish medium texture, well drained calcareous, shallow on hills, deep soils in valleys
V	Humid south eastern plain	2.7	Kota, Jhalawar, Bundi, Baran	Sorghum, soya bean	Wheat, mustard	Black of alluvial origin, clay loam, groundwater salinity

names like red sandy loam deep soils) of the region are divided into the deep brown loamy, medium brown loamy, deep dark brown sandy and shallow red gravelly loam.

3.3. Climate data and bias-correction method

The gridded datasets from the Indian Meteorological Department (IMD) and CORDEX-SA data are used in the present study. The resolution of IMD precipitation and temperature data is $0.5 \times 0.5°$ and $1 \times 1°$ respectively. The World Climate Research Programme (WCRP) Coordinated Regional Climate Downscaling Experiment (CORDEX; http://www.cordex.org/) provided the dataset for South Asia region and used by the scientific community to conduct studies related to climate change impacts at regional and spatial scales. Taylor et al. (2012) provided an overview of CORDEX dataset and downscaled climate scenarios for the South Asia region that are derived from the Atmosphere-Ocean coupled General Circulation Model (AOGCM) conducted under the Coupled Model Inter-comparison Project Phase 5 (CMIP5). The purpose of these datasets is to provide a set of high resolution (50 km) regional climate change projections which can be used to evaluate climate change impacts on various sectors. These are also useful to study processes that are sensitive to finer-scale climate gradients. CORDEX-SA data are downloaded from Center for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology, Pune, India. For future crop yield prediction, the ensemble driving GCMs, i.e. CNRM-CM5, CCSM4 and MPI-ESM-LR of RCP4.5 and RCP8.5 scenarios are used. Information about the CORDEX South Asia Regional Climate Model is presented in Table 3.

The RCPs (Representative Concentration Pathways) are named according to radiative forcing and estimation are based on the forcing of greenhouse gases. The four selected RCPs were considered to be representative of the literature, and included one mitigation scenario leading to the lowest forcing level scenario (RCP2.6), two medium stabilization scenarios (RCP4.5/RCP6) and one very high baseline emission scenarios (RCP8.5). RCP4.5 stabilization without overshoot pathway to 4.5 W/m^2 (~650 ppm CO_2 eq) at stabilization after 2100 (Clarke et al., 2007;

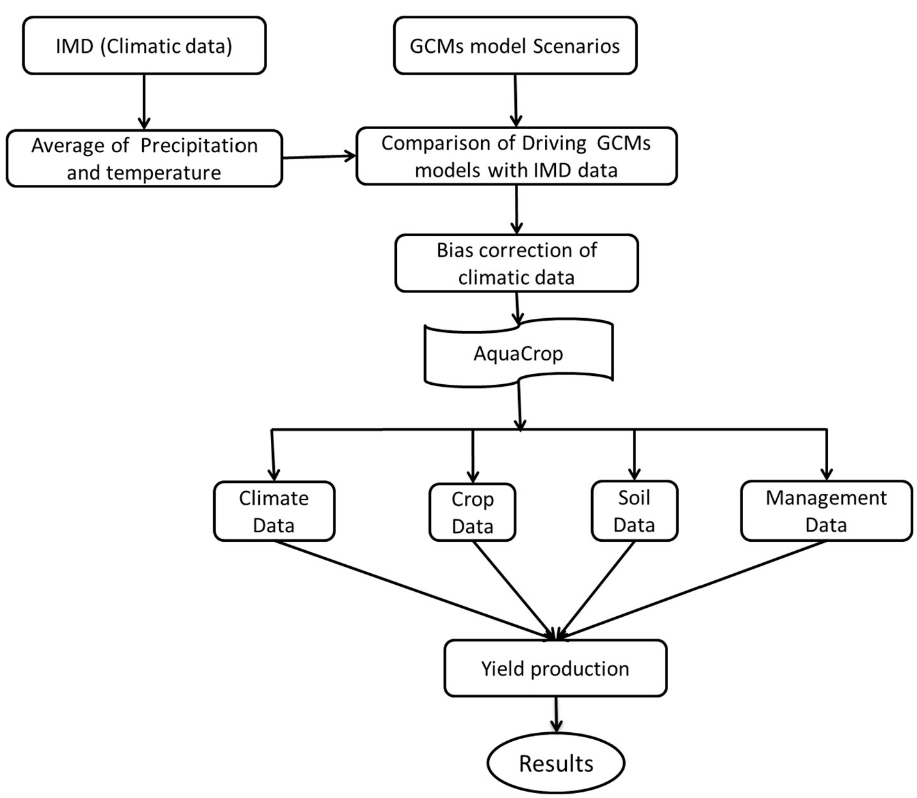

Fig. 3. Flowchart of the methodology framework used in the study.

Table 2
Characteristics and crops development stage of maize, wheat and barley.
Source: Food and Agriculture Organization United States (FAO).

Crop characteristic	Initial	Crop development	Mid-season	Late	Total	Plant date
Maize crop						
Stage length days	25	40	35	35	130	Jun (B)–Jul (E)
Depleting coefficient	0.5	0.5	0.5	0.8	–	–
Root depth	0.3	≫	≫	1	–	–
Crop coefficient	0.3	≫	1.2	0.5	–	–
Yield response factor	0.4	0.4	1.3	0.5	1.25	–
Wheat crop						
Stage length days	40	30	40	20	130	Nov (B)–Dec (E)
Depleting coefficient	0.6	≫	0.6	0.9	0.55	–
Root depth	0.3	≫	≫	1.4	–	–
Crop coefficient	0.4	≫	1.15	0.4	–	–
Yield response factor	0.2	0.6	0.5	–	1.15	–
Barley crop						
Stage length days	40	30	40	20	130	Nov (B)–Dec (E)
Depleting coefficient	0.6	≫	0.6	0.9	0.55	–
Root depth	0.4	≫	≫	1.5	–	–
Crop coefficient	0.5	≫	1.15	0.5	–	–
Yield response factor	0.3	0.5	0.5	–	1.25	–

Wise et al., 2009). RCP8.5 is rising radiative forcing pathway leading to 8.5 W/m^2 (~1370 ppm CO_2 eq) by 2100 (Riahi et al., 2007).

The Delta method is used for the bias-correction of future weather data from the crop yield projections. This method is used for climate scenarios to improve their quality of maximum and minimum temperature and precipitation before using the impact assessment of AquaCrop model. The method is used for bias-correction by adding (or multiplying) the observed data in the baseline period for temperature and precipitation respectively (Graham et al., 2007; Weiland et al., 2010; Watanabe et al., 2012)

$$x_{cor,i,t} = x_{h,i} + \mu_f - \mu_b \qquad \text{(For temperature)} \tag{1}$$

$$x_{cor,i,r} = x_{h,i} \times \frac{\mu_f}{\mu_b} \qquad \text{(For precipitation)} \tag{2}$$

where $x_{cor,\,i}$ and $x_{h,\,i}$ ($i = 1, 2, \ldots, 30$ years) denotes the bias-corrected and observed datasets in the baseline period, respectively. The subscript b, f and h indicate the climate model data for the baseline period, future period, and observed historical data (Watanabe et al., 2012).

3.4. AquaCrop model

AquaCrop model is used to calculate the yield of all the three crops for historical period of 30 years (1981–2010) and then compared with observed data. IMD climatic data and the ensemble CORDEX-SA climate models data are used in the model. AquaCrop model is simulated by the FAO to know the total yield response to water (Steduto et al., 2009; Raes et al., 2009). It is designed to balance the accuracy, simplicity, robustness and condition of water of a particular area, as water is a key limiting factor in crop production. Raes et al. (2009) and Steduto et al. (2009) explained the background information and theory of AquaCrop. The latest version of the AquaCrop model (version 5, October 2015) has been used in this study (FAO, 2015). For the different crops, many authors used the AquaCrop for the yield and biomass prediction like the maize crop (Raes et al., 2009; Steduto et al., 2009) and wheat (Jamieson et al., 1998) and model has been profoundly calibrated and validated (Hsiao et al., 2009; Heng et al., 2009). Daily simulation of crop growth development in AquaCrop is integrated with the daily simulation of soil water balance, which provides a robust and accurate platform for modeling different agricultural management scenarios where water is a limiting factor in crop production (Steduto et al., 2009). The model uses separate input components of climate data, crop parameters, management (irrigation and field), soil (soil characteristics and groundwater) for simulating crop yield.

Fig. 4 presents the various components of AquaCrop to represent the soil–plant–atmosphere continuum and the different steps like phenology, canopy cover, transpiration, biomass production, and final yield.

AquaCrop model is based on the cumulative actual crop transpiration during the growing season (T_r) and normalized water productivity (WP*) for simulating total biomass (B) as Eq. (3) (Steduto et al., 2009).

$$B = WP^* \times \sum T_r \tag{3}$$

The harvestable yield (Y) is a function of B and Harvest Index (HI) Eq. (4), such that distinguishes the effect of environmental stresses on B and HI.

$$Y = B \times HI \tag{4}$$

3.5. Model evaluation

There are several statistics available to evaluate and compare the simulated and observed results of the model (Heng et al., 2009; Steduto et al., 2009). Evaluation of the AquaCrop model (Jamieson et al., 1991; Loague and Green, 1991) was performed using two statistical measures, namely Root Mean Square Error (RMSE) and Modeling Efficiency (ME), as described by Rinaldi et al. (2003):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}} * \frac{100}{\overline{O}} \tag{5}$$

$$ME = \frac{\left[\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2 - \sum_{i=1}^{n} (P_i - O_i)^2\right]}{\left[\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2\right]} \tag{6}$$

Table 3
List of CORDEX South Asia Regional Climate Model (RCM) experiments.

Experiment name	RCM description	Driving GCM	Contributing institute	Resolution
CCAM (CNRM)	Commonwealth Scientific and Industrial Research Organisation (CSIRO), Conformal-Cubic	CNRM-CM5	CSIRO Marine and Atmospheric Research, Melbourne, Australia	0.44 × 0.44°
CCAM (CCSM)	Atmospheric Model (CCAM; Mcgregor and Dix, 2001)	CCSM4		0.44 × 0.44°
CCAM (MPI)		MPI-ESM-LR		0.44 × 0.44°

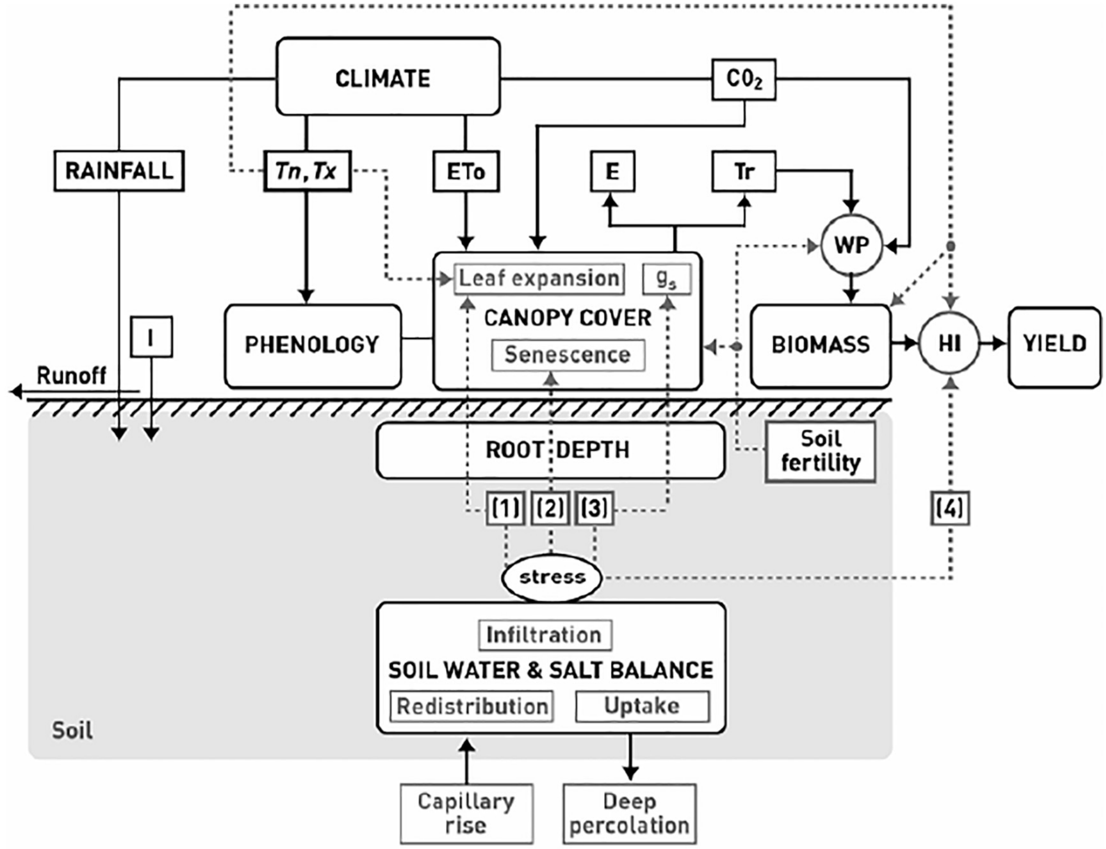

Fig. 4. Flowchart and methodology of AquaCrop model (Steduto et al., 2009). Note: I, irrigation; Tn, minimum air temperature; Tx, maximum air temperature; ETo, reference evapotranspiration; E, soil evaporation; Tr, canopy transpiration; gs, stomatal conductance; WP, water productivity; HI, Harvest Index; CO_2, atmospheric carbon dioxide concentration; (1), (2), (3), (4), water stress response functions for leaf expansion, senescence, stomatal conductance and Harvest Index respectively.

where P_i, O_i, and $\bar{o}$ are predicted, observed and observed mean value of the crop yield. RMSE gives the relative difference of simulated and observed data given of measure in the percentage (%).

The model accuracy can be divided into different groups based on RMSE values, i.e., excellent (<10%), good (10–20%), fair (20–30%), poor (>30%) (Jamieson et al., 1991; Andarzian et al., 2015). The lower limit for both RMSE and ME is zero. The maximum value for ME is 1. If ME is less than zero the simulated values are worse than simply using the observed mean values. A positive value for ME indicates that the model performs better than merely applying the observed mean (Loague and Green, 1991).

4. Results and discussion

4.1. Precipitation

Delta method was used for the bias correction of the future data then that data compare to the historical IMD data. Fig. 5 shows the monthly variation of the precipitation data in the historical (model), bias corrected historical (model) and IMD observed. The ability of climate models is to represent the physical processes of the climate system efficiently. There are still systematic deviations (biases) between simulated and observed climate variables, i.e. adjusting the simulations for these

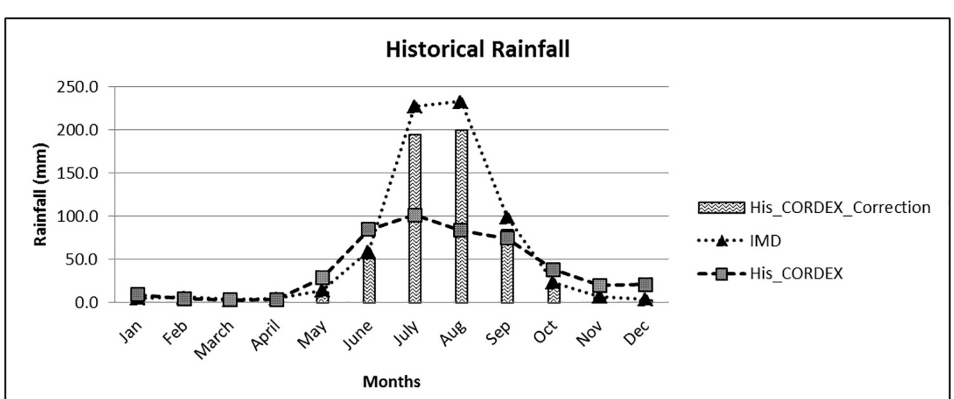

Fig. 5. IMD historical, CORDEX-SA historical and bias corrected historical precipitation period.

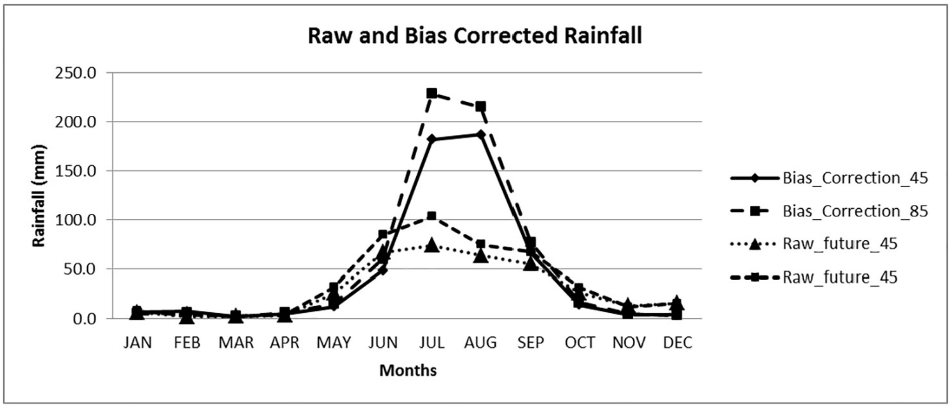

Fig. 6. Shows the CORDEX-SA future raw data and bias corrected future precipitation data of RCP4.5 and RCP8.5.

biases is important for climate change impact and adaptation studies, as these are often based on projections of variables that depend on crossing absolute thresholds e.g., minimum and maximum temperature, numbers of frost days, summer days, and precipitation days. Fig. 6 shows the raw and bias corrected future data of the scenarios RCP4.5 and RCP8.5 for the period 2021–2050. Fig. 7 shows the variation in the bias corrected future data of historical (model), RCP4.5, RCP8.5 with respect to IMD observed. The values of ME and RMSE before correction are −18.0 mm and 58 mm which reduced to −8.1 mm and 14.3 mm after using the bias correction method. In Fig. 8 the changes in precipitation are shown in both scenarios of RCP4.5 and RCP8.5 for the period 2021–2050, the maximum precipitation change showing in the month of August (−45.9 mm) of the RCP4.5 scenario and in RCP8.5 scenario the precipitation change showing in the month of September (−21.9 mm) with respect to historical period (1981–2010). Precipitation change in scenarios RCP4.5 and RCP8.5 are observed in two different months. It is well known that every climate model is unique and provide us different scenarios. The possible reasons for this difference are radiative forcing, physics of the earth climate model, and parameterization in the model framework. The study shows that, in future the precipitation is decreased in monsoon season and increased in winter months with respects to historical precipitation.

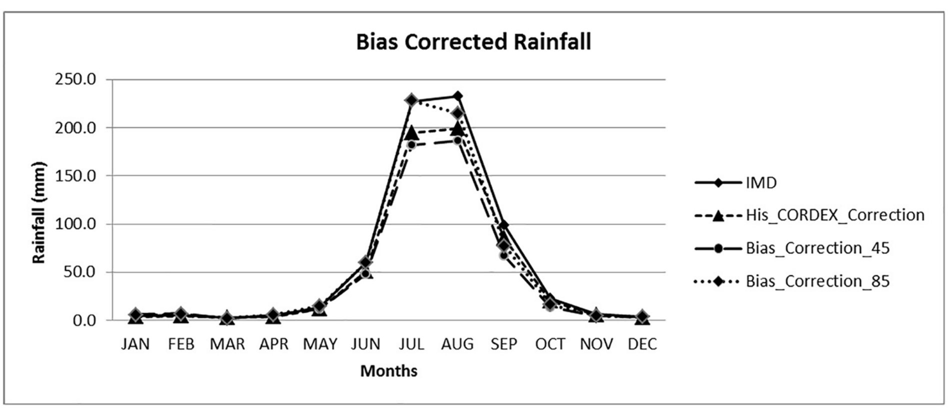

Fig. 7. Ensemble CORDEX-SA future raw data and bias corrected future precipitation data of RCP4.5 and RCP8.5.

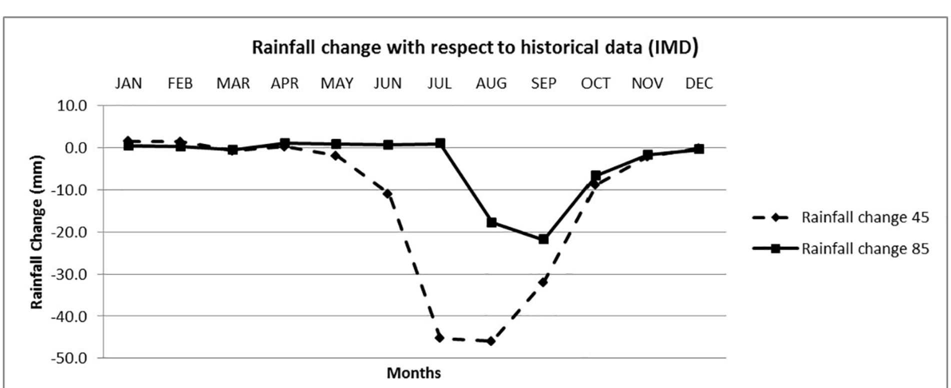

Fig. 8. Precipitation change of future precipitation data of RCP4.5 and RCP8.5 with respect to historical period (1981–2010).

Table 4
Climatic parameters information of RCP4.5 and RCP8.5 scenarios.

Time period	CO_2 (ppm)	Tmax (°C)	Tmin (°C)	Time period	CO_2 (ppm)	Tmax (°C)	Tmin (°C)
1981–2010	363.09	32.78	18.77	1981–2010	363.09	32.78	18.77
2021–2050 (RCP4.5)	449.43	33.28	20.14	2021–2050 (RCP8.5)	473.43	33.58	20.07
Change	86.34	0.5	1.37	Change	110.34	0.8	1.3

4.2. Atmospheric CO_2 concentration and temperature

For the present study, the mean CO_2 concentration is used as 363.09 ppm for the period 1981–2010 (IPCC, 2007) and for the future period, value of CO_2 concentration is taken from the model scenarios. The CO_2 concentration in RCP4.5 scenario is 449.43 ppm and in RCP8.5 scenario is 473.34 ppm for the period 2021–2050 as shown in Table 4. The change in CO_2 concentration of RCP4.5 is 86.34 ppm and RCP8.5 is 110.34 ppm with respect to the baseline period (1981–2010).

Figs. 9 and 10 showed the variation in temperature for the future period 2021–2050 in both scenarios (RCP4.5 and RCP8.5) with respect to the historical period (1981–2010) and observed that all the ensemble models agree on a future temperature rise. The rising trend of temperature and increased precipitation shortage are observed in RCP4.5 and RCP8.5 scenarios for the period 2021–2050. Moreover, the projected change in maximum and minimum temperature varies from 0.5 °C to 0.8 °C and 1.37 °C to 1.3 °C in RCP4.5 and RCP8.5 scenario, where the minimum temperature increases as compared to maximum temperature as shown in Table 4.

4.3. Model evaluation results

AquaCrop model simulation is used to observe the crops yield in the historical period for the model calibration and predict the future yield production. The period of sowing and harvesting of crops are different with sowing date of wheat and barley are taken same, i.e. 6th November, whereas maize is rain-fed crop the sowing date is 5th July and run for the historical period (2000−2010) and future period (2021–2050). The model had good performance (RMSE between 10 and 20% and ME > 0) in simulating wheat, barley and maize yields. Table 6 presents the RMSE and ME of the different crops. All the RMSE values are found to be <20% and falls in the category of good accuracy of the model simulation. RMSE values of wheat, barley and maize crops are 11.99, 16.15 and 19.13 respectively. Similarly, ME values of wheat, barley and maize crops are 0.44, 0.09, and 0.91 respectively.

4.4. Yield projections

In order to project yield for a future period, model parameters are used as similar to calibrated model except for climate data of temperature and precipitation. For future, the two scenarios (RCP4.5 and RCP8.5) are used to predict the yields of these three crops and their significant information are shown in Table 5.

The relative yield changes for maize, barley and wheat are shown in Table 6. The predicted yields of wheat increased from 2.33 tons/ha in the baseline period to 3.90 tons/ha in RCP4.5 scenario and 3.50 tons/ha in RCP8.5 scenario. The changes show the increasing trend of the yield of wheat for two scenarios with respect to the baseline periods, i.e. 1.56 tons/ha and 1.16 tons/ha, respectively.

Table 6 present the change and percentage change in yield of three crops with respect to their historical yield. The production of maize crop is simulated 1.39 tons/ha for the baseline period. In the future period (2021–2050), the yield of maize may increase to 1.49 tons/ha in RCP4.5 scenario and 1.67 tons/ha in RCP8.5 scenarios. The percentage changes are about 7.1% and 20.4% for both the scenarios. Barley crop is

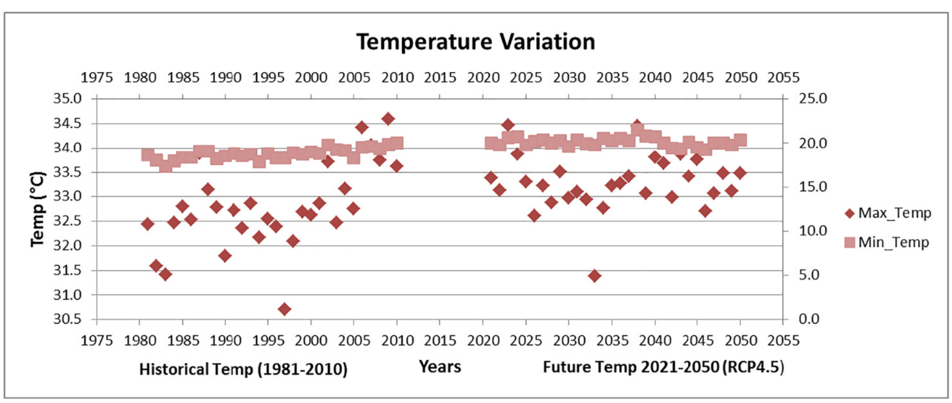

Fig. 9. Variation of the future temperature data of RCP4.5 with respect to historical period (1981–2010).

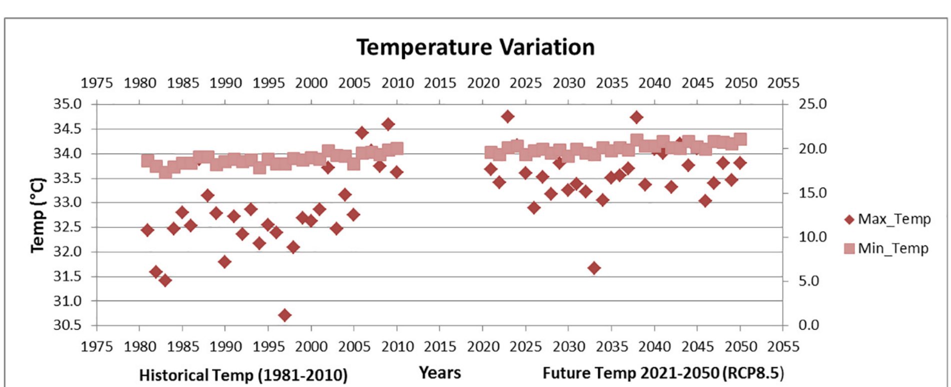

Fig. 10. Variation of the future temperature data of RCP8.5 with respect to historical period (1981–2010).

Table 5
Major crops information of the study area.

Crop	Plant type	Sowing	Harvesting	Sowing date	No. of days	Time periods of run (historical)	Time periods of run (future)
Wheat	C3	Nov (B)–Dec (E)	Mar (B)–May (E)	06-Nov	130 days	1981–2010	2021–2050
Maize	C4	Jun (B)–Jul (E)	Oct (B)–Nov (E)	05-Jul	130 days	1981–2010	2021–2050
Barley	C3	Nov (B)–Dec (E)	Mar (B)–May (E)	06-Nov	130 days	1981–2010	2021–2050

Note: B means beginning date and E means end date.

Table 6
Changes and percentage changes in simulated future (a) wheat (b) maize and (c) barley yield in the RCPs scenarios.

Crops	Historical	RCP4.5	RCP8.5	Change	Change	Change	% change (RCP4.5)	% change (RCP8.5)	RMSE	ME
	1981–2010 (1)	2021–2050 (2)	2021–2050 (3)	(2 − 1)	(3 − 1)	(2 − 3)				
Wheat	2.33	3.9	3.5	1.56	1.16	0.4	66.8	49.8	11.99	0.44
Maize	1.39	1.49	1.67	0.1	0.28	−0.19	7.1	20.4	19.13	0.91
Barley	1.93	2.9	2.83	0.97	0.9	0.07	49.9	46.3	16.15	0.09

Note: RMSE = Root Mean Square Error, ME = Modeling Efficiency.

C3 plants and the production of the crop in the historical period is simulate 1.93 tons/ha. AquaCrop model predicted the future period yield of 2.90 tons/ha in RCP4.5 and 2.83 tons/ha in RCP8.5. The possible reason for the increase in production is increase in temperature as it is good for the phenological growth of crop considering the climate of the study area.

5. Conclusions

The present study investigated the importance of AquaCrop model to assess climate change impact on different crop yield at the basin scale. This research was carried out to project the impact of climate change on yield of wheat, barley and maize in the semi-arid Banas river basin of Rajasthan state, India. Ensemble mean of three climate models taken from CORDEX-SA is used in the crop model. Future ensemble climatic models show warmer climate change scenarios and atmospheric CO_2 for both scenarios (RCP4.5 and RCP8.5). The impact of RCP4.5 and RCP8.5 scenarios on wheat, barley and maize growth reveals a progressive increase trend of the crops. The most significant growth of crop yield is observed in the wheat followed by barley and maize in the RCP4.5 scenario for the period 2021–2050 with respect to baseline period (1981–2010). Similar patterns of growth also observed in all the three crops in the RCP8.5 scenarios. The average yield will increase, but this will occur in a non-linear manner. These results suggest that regional projections with crop models can be improved by using more information from field data. Results are important in understanding the possible impact of climate change on crop yield and helpful in developing knowledge for stakeholders and planners to develop appropriate plans and strategies.

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References

Abedinpour, M., Sarangi, A., Rajput, T.B.S., Singh, M., Pathak, H., Ahmad, T., 2012. Performance evaluation of AquaCrop model for maize crop in a semi-arid environment. Agric. Water Manag. 110, 55–66.
Agriculture Department of Rajasthan, Government of India, d. http://www.agriculture.rajasthan.gov.in/content/agriculture/en/Agriculture-Department-portal/departmental-introduction/agro-climatic-zones.html.
Andarzian, B., Hoogenboom, G., Bannayan, M., Shirali, M., Andarzian, B., 2015. Determining optimum sowing date of wheat using CSM-CERES-Wheat model. J. Saudi Soc. Agric. Sci. 14 (2), 189–199.
Bird, D.N., Benabdallah, S., Gouda, N., Hummel, F., Koeberl, J., La Jeunesse, I., Meyer, S., Prettenthaler, F., Soddu, A., Woess-Gallasch, S., 2016. Modelling climate change impacts on and adaptation strategies for agriculture in Sardinia and Tunisia using AquaCrop and value-at-risk. Sci. Total Environ. 543, 1019–1027.
Challinor, A.J., Simelton, E.S., Fraser, E.D., Hemming, D., Collins, M., 2010. Increased crop failure due to climate change: assessing adaptation options using models and socio-economic data for wheat in China. Environ. Res. Lett. 5 (3), 034012.
Clarke, L.E., Edmonds, J.A., Jacoby, H.D., Pitcher, H., Reilly, J.M., Richels, R., 2007. Scenarios of Greenhouse Gas Emissions and Atmospheric Concentrations. Sub-report 2.1a of Synthesis and Assessment Product 2.1. Climate Change Science Program and the Subcommittee on Global Change Research, Washington DC.
Cure, J.D., 1985. Carbon dioxide doubling responses: a crop survey. In: Strain, B.R., Cure, J.D. (Eds.), Direct Effects of Increasing Carbon Dioxide on vegetation. DOE/ER-0238. US Dep. of Energy, Washington, DC, USA, pp. 99–116.
Cure, J.D., Acock, B., 1986. Crop responses to carbon dioxide doubling: a literature survey. Agric. For. Meteorol. 38, 127–145.
Easterling, W.E., Aggarwal, P.K., Batima, P., Brander, K.M., Erda, L., Howden, S.M., Kirilenko, A., Morton, J., Soussana, J.F., Schmidhuber, J., Tubiello, F.N., 2007. Food, fibre and forest products. Climate Change 273–313.
FAO, 2008. The state of food and agriculture. ftp://ftp.fao.org/docrep/fao/011/i0291e/i0291e00a.pdf, Accessed date: January 2017.
FAO, 2009. AquaCrop: the FAO Crop-model to simulate yield response to water. http://www.fao.org/nr/water/aquacrop.html, Accessed date: January 2017.
FAO, 2015. About AquaCrop. http://www.fao.org/nr/water/aquacrop_about.html, Accessed date: 26 December 2015.
FAOSTAT, 2000. Food and Agriculture Organization Statistical Database. Internet: http://apps.fao.org/page/collections?subset=agriculture.
Farahani, H.J., Izzi, G., Oweis, T.Y., 2009. Parameterization and evaluation of the AquaCrop model for full and deficit irrigated cotton. Agron. J. 101 (3), 469–476.
Food and Agriculture Organization of the United Nations (FAO), 2003. The state of food insecurity in the world. Rome, Italy. http://www.fao.org/docrep/006/j0083e/j0083e00.htm.
Goudriaan, J., Unsworth, M.H., 1990. Implications of increasing carbon dioxide and climate change for agricultural productivity and water resources. Impact of carbon dioxide, trace gasses, and climate change on global agriculture. ASA Special Publication No. 53. American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America, Madison, USA, pp. 111–130.
Graham, L.P., Andréasson, J., Carlsson, B., 2007. Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods–a case study on the Lule River basin. Clim. Chang. 81, 293–307.
Hanjra, M.A., Qureshi, M.E., 2010. Global water crisis and future food security in an era of climate change. Food Policy 35 (5), 365–377.
Heng, L.K., Hsiao, T., Evett, S., Howell, T., Steduto, P., 2009. Validating the FAO AquaCrop model for irrigated and water deficient field maize. Agron. J. 101 (3), 488–498.
Hsiao, T.C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D., Fereres, E., 2009. AquaCrop – the FAO crop model to simulate yield response to water: III. Parameterization and testing for maize. Agron. J. 101, 448–459.
IPCC (Intergovernmental Panel on Climate Change), 2007. Climate change 2007: synthesis report. Fourth Assessment Report Available online:. http://www.ipcc.ch/ipccreports/ar4-syr.htm (51 pp.).
Jamieson, P.D., Porter, J.R., Wilson, D.R., 1991. A test of the computer simulation model ARCWHEAT1 on wheat crops grown in New Zealand. Field Crop Res. 27, 337–350.
Jamieson, P.D., Semenov, M.A., Brooking, I.R., Francis, G.S., 1998. Sirius: a mechanistic model of wheat response to environmental variation. Eur. J. Agron. 8, 161–179.
Knox, J., Hess, T., Daccache, A., Wheeler, T., 2012. Climate change impacts on crop productivity in Africa and South Asia. Environ. Res. Lett. 7 (3), 034032.
Kumar, P., Sarangi, A., Singh, D.K., Parihar, S.S., 2014. Evaluation of AquaCrop model in predicting wheat yield and water productivity under irrigated saline regimes. Irrig. Drain. 63 (4), 474–487.

Kummu, M., de Moel, H., Porkka, M., Siebert, S., Varis, O., Ward, P.J., 2012. Lost food, wasted resources: global food supply chain losses and their impacts on freshwater, cropland, and fertiliser use. Sci. Total Environ. 438, 477–489.

Lin, B.B., 2011. Resilience in agriculture through crop diversification: adaptive management for environmental change. Bioscience 61 (3), 183–193.

Loague, K., Green, R.E., 1991. Statistical and graphical methods for evaluating solute transport models: overview and application. J. Contam. Hydrol. 7 (1–2), 51–73.

Lobell, D.B., Sibley, A., Ortiz-Monasterio, J.I., 2012. Extreme heat effects on wheat senescence in India. Nat. Clim. Chang. 2 (3), 186–189.

Mcgregor, J.L., Dix, M.R., 2001. The CSIRO conformal-cubic atmospheric GCM, In IUTAM Symposium on Advances in Mathematical Modelling of Atmosphere and Ocean Dynamics. Springer, Dordrecht, pp. 197–202.

Mkhabela, M.S., Bullock, P.R., 2012. Performance of the FAO AquaCrop model for wheat grain yield and soil moisture simulation in Western Canada. Agric. Water Manag. 110, 16–24.

Pawar, G.S., Kale, M.U., Lokhande, J.N., 2017. Response of AquaCrop model to different irrigation schedules for irrigated cabbage. Agric. Res. 6 (1), 73–81.

Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., 2009. AquaCrop the FAO crop model to simulate yield response to water: II. Main algorithms and software description. Agron. J. 101 (3), 438–447.

Riahi, K., Grübler, A., Nakicenovic, N., 2007. Scenarios of long-term socio-economic and environmental development under climate stabilization. Technol. Forecast. Soc. Chang. 74, 887–935.

Rinaldi, M., Losavio, N., Flagella, Z., 2003. Evaluation and application of the OILCROP–SUN model for sunflower in southern Italy. Agric. Syst. 78 (1), 17–30.

Rotter, R.P., Carter, T.R., Olesen, J.E., 2011. Crop–climate models need an overhaul. Nat. Clim. Chang. 1, 175–177.

Saad, A.M., Mohamed, M.G., El-Sanat, G.A., 2014. Evaluating AquaCrop model to improve crop water productivity at North Delta soils, Egypt. Adv. Appl. Sci. Res. 5 (5), 293–304.

Sen, A.K., Abraham, C.T., 1966. Crop belts and cropping patterns of Rajasthan. Ann. Arid Zone 5 (1), 105–116.

Simba, F.M., Mubvuma, M., Murwendo, T., Chikodzi, D., 2013. Prediction of yield and biomass productions: a remedy to climate change in semi-arid regions of Zimbabwe. Int. J. Adv. Agric. Res. 1, 14–21.

Singh, A., Saha, S., Mondal, S., 2013. Modelling irrigated wheat production using the FAO AquaCrop model in West Bengal, India, for sustainable agriculture. Irrig. Drain. 62 (1), 50–56.

Smith, P., 2013. Delivering food security without increasing pressure on land. Glob. Food Sec. 2 (1), 18–23.

Steduto, P., Hsiao, T.C., Raes, D., Fereres, E., 2009. AquaCrop—the FAO crop model to simulate yield response to water: I. Concepts and underlying principles. Agron. J. 101 (3), 426–437.

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc. 93 (4), 485–498.

Watanabe, S., Kanae, S., Seto, S., Yeh, P.J.F., Hirabayashi, Y., Oki, T., 2012. Intercomparison of bias-correction methods for monthly temperature and precipitation simulated by multiple climate models. J. Geophys. Res. Atmos. 117 (D23).

Weiland, F.S., Van Beek, L.P.H., Kwadijk, J.C.J., Bierkens, M.F.P., 2010. The ability of a GCM-forced hydrological model to reproduce global discharge variability. Hydrol. Earth Syst. Sci. 14 (8), 1595.

Wise, M., Calvin, K., Thomson, A., Clarke, L., Bond-Lamberty, B., Sands, R., Smith, S.J., Janetos, A., Edmonds, J., 2009. Implications of limiting CO_2 concentrations for land use and energy. Science 324, 1183–1186.